CHAPTER 5

CONCLUSION

This thesis deals with ARMA model selection in time series with and without seasonality. The major focus is on evaluating and proposing alternatives or modifications to parts of the usual Box-Jenkins (1970) approach to time series modeling. Their approach boils down to three steps, i.e. the identification of a tentative model, its estimation, and the application of checks for residual autocorrelation to see whether the model is adequate and which possible modification routes can be pursued. The approach assumes the stationarity of the time series, and it is therefore advocated to consider first differences when the nonseasonal series looks nonstationary, and to take first and seasonal differences when the seasonal series does.

Chapter 3 deals with several of the steps in this conventional method. First, it is shown on the basis of some simulation experiments that a true but unknown data generating process can have a large impact on the selection between two incorrect models, but that, e.g., the outcomes of autocorrelation checks are not effected. Second, since the ARMA class of models assumes uncorrelated residuals as well as linearity, homoscedasticity, and the absence of outliers, it seems reasonable to check all these basic requirements. Finally, it is argued that since time series models are used for several purposes, such as forecasting and explanation, it also seems natural to select models with corresponding criteria. Together this gives rise to a proposal for an alternative model building strategy which includes three steps, i.e. the construction of a set of models, the diagnostic checking of these using a battery of tests, and the selection of a temporarily adequate model with criteria related to model use. These criteria should treat the models in a symmetrical way, which means that no null hypothesis has to be defended. This strategy is the leading thread running through chapter 3, and the sections 3.3 though 3.5. deal with each of these three alternative steps. In fact, this method may be useful when the role of an econometrician is as it is described by Kloek in his foreword to Lempers (1971):

> "... Then his position very much resembles that of a person whose goal it is to be the owner of a winning horse. If he can only afford to buy one horse, he is in the position of the classical hypothesis-tester who accepts one hypothesis and rejects all others. But if he is richer he can do better; he can keep a whole racing stable and enter for a race those horses which seem to be in the best condition at the moment. And from time to time he can replace certain horses that have a poor past performance and hardly better prospects."

An empirical example of the selection of an AR model for the unemployment rate series for the U.S. is used to illustrate various elements of the steps in the strategy. The obvious drawback of the method, when compared with the Box-Jenkins way of modeling, is that it involves several more computations and decisions. Given the large scale use of ARMA time series models in forecasting and, currently, in dynamic econometric model building, these extended efforts seem worthwhile.

Specific attention in chapter 3 is paid to the decision whether a variable has to be differenced or not. The tradition of straightforwardly differencing a series in case its autocorrelation function dies out only slowly seems to have been replaced nowadays by automatically applying the Dickey and Fuller (1979) approach to testing for unit roots. This method assumes the adequacy of univariate AR models to describe many economic time series. In section 3.3, I discuss the impact of this assumption in more detail. The major recommendations are to base unit root inference on multivariate models, and when these are not readily available, to consider a range of AR models for sensitivity analysis purposes. Additionally, a simple test procedure is presented to check whether one has erroneously differenced an MA model.

Chapter 4 concentrates on model selection strategies for time series with seasonality. In fact, the major focus is on modeling the seasonal movements in these time series. In the first section of this chapter I survey several of these models. I propose a model selection device which can handle some of the simple models. Evidence obtained from simulations as well as from empirical series shows that this method may often be useful. However, there are occasions in which it may not be suitable, and then one might want to rely on the method proposed in Hylleberg *et al.* (1990), which is a testing procedure for the presence of seasonal unit roots. This study considers quarterly time series only, and extensions to monthly and bimonthly time series are therefore presented in section 4.2. Furthermore, some empirical power investigations are carried out, and it appears that the method may reasonably well be able to reject the hypothesis of seasonal unit roots when they are absent indeed. Section 4.3 shows that erroneously doubly differencing a series, while a model with only first differences and seasonal dummies is adequate, can have an effect on forecasting, on multivariate time series model building, and on linearity.

The final section of chapter 4 introduces a new and general class of models for seasonal time series. Essentially, this class is given by a vector autoregressive model for the observations per season when they are viewed as separate series. It appears that this class not only provides intermediate cases between currently considered models, but also that the selection between the usual nonnested models can be done quite easily. An important side benefit is that this multivariate approach introduces a new way of plotting seasonal time series which may provide some *a priori* visual evidence with respect to possibly appropriate models. An extension to bivariate time series appears to be straightforward.

There are of course many issues for further research in model selection in seasonal time series. Examples are the investigation of the sensitivity of the selection methods to outlying observations, to structural breaks, and to other data irregularities. Furthermore, a large scale empirical size and power study, in which the univariate and bivariate methods are compared also relative to each other, is of interest. Anyhow, it may be that the selection strategies given in chapter 4, as well as those for nonseasonal time series in chapter 3, can facilitate the sometimes rather difficult decision on the most appropriate empirical time series model.